Do Managers Always Know Better? An Examination of the Relative Accuracy of Management and Analyst Forecasts

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Abstract

In this paper we examine the relative accuracy of management and analyst forecasts. We predict and find that analysts' information advantage resides at the macroeconomic and industry level. They provide more accurate long-horizon earnings forecast than management when the firm's fortunes move in concert with macroeconomic factors such as gross domestic product, energy costs and interest rates and when the firm's sales growth is more synchronous with its industry's aggregate sales growth. In contrast, we expect and find that management's information advantage resides at the firm level. Their forecasts are more accurate than analysts when management's actions, which affect reported earnings, are difficult to anticipate by outsiders. Examples include when the firm's inventories are abnormally high, it has excess capacity, or the firm is experiencing a loss.

1. Introduction

Analysts' forecasts and management's forecasts are two important sources of information used by investors when developing firm-level earnings expectations. However, the weight that ought to be assigned to each (when both are provided, but differ) is unclear, given how little is known about the relative accuracy of analyst and management forecasts.

One would expect that managers have a distinct advantage over analysts in forecasting earnings. They are insiders running the firm making key business decisions. As such, it is not surprising that much of the prior literature presumes that management has an information advantage over analysts and thus provides more accurate earnings forecasts (e.g., Altschuler 2009). However, given one of analysts' primary functions is to provide earnings forecasts and given the amount of resources devoted to this process, it is not a foregone conclusion that managers' information set is superior. In fact, Hutton and Stocken (2010) document (by happenstance in their Table 3) that management's forecasts are more accurate than analysts' forecasts only about 50 percent of the time. This empirical observation begs the question: *When are analysts' forecasts more accurate than management's forecasts, given the inside information managers possess?*

In this paper we attempt to shed some light on this question by examining the relative accuracy of analyst and management long-horizon earnings forecasts. We match up the management forecast with the prevailing non-stale analyst earnings forecasts issued for the same fiscal period.[1] Our matching procedure ensures that the management and analyst forecasts have the same forecast horizon and are forecasting the same earnings construct.

[1] We define non-stale analyst forecasts as those made within 30 days *prior* to the management earnings forecasts. For our primary set of tests we give management the advantage, in that management's forecast is made after the analysts' forecasts.

Drawing on the extant analyst forecast literature and management guidance literature, we conjecture when analysts' forecasts are likely to be more accurate than management's and vice versa. Specifically, we expect and find that analysts' information advantage resides at the macroeconomic and industry level, where a firm's operations are highly exposed to forces outside managers' control (e.g., cyclical, input prices, regulation and competition). Analysts provide more accurate long-horizon earnings forecast when the firm's fortunes move with broad macroeconomic factors or depend on input prices that are often forecasted by macroeconomists, such as energy costs and interest rates. Analysts also have more accurate forecasts when the firm's sales growth is highly synchronous with the industry's aggregate sales growth.

In contrast, we expect and find that managers' information advantage as insiders running the firm is most pronounced in situations where analysts find it hard to anticipate managers' response to unusual operating situations, such as when the firm faces abnormally inventory buildup, when it experiences excess capacity, or in an off-equilibrium loss year. Unable to anticipate management's response, analysts find it exceedingly difficult to anticipate the effect of management's response on reported earnings.

We make several contributions to the literature: To our knowledge, we are the first to highlight the fact that management's forecasts are more accurate than analysts' forecasts only about 50% of the time. By doing so we cast doubt on the premise in the literature that management has an information advantage over analysts that permits its earnings guidance to substitute for the private information acquired by analysts (Diamond 1985, Altschuler 2009). Second, we document the firm characteristics and operating situations associated with analysts providing more accurate long-horizon forecasts than management. Third, we document the circumstances under which management's information advantage leads to a clear forecasting advantage over sell-side analysts. These latter two empirical contributions ought to be useful for informing investors about the relative weights to assign to each type of forecast when forming their own earnings expectations.

The paper proceeds as follows: In section 2 we review the relevant literatures, outline our conjectures about the relative information advantage of managers versus analysts, and state our empirical predictions. Section 3 outlines our sample selection and variable definitions. Section 4 presents our empirical analysis; section 5 our conclusions.

2. Literature Review & Empirical Predictions

While the literatures on analyst forecasts and managerial earnings guidance are extensive, few prior research papers compare analyst and management forecasts. Instead, prior research often assumes that management forecasts are more accurate than analysts' forecasts, because of the presumed information advantage of management. For instance, Altschuler (2009, p. 12) notes:

> *Even when management's forecasts are relatively inaccurate, it is unlikely that analysts can produce more accurate forecasts because of the information advantage managers have over analysts.*

Based on this presumption, Altschuler argues that the anticipation of a management forecast may reduce analysts' incentive to acquire private information because the information disclosed by management is a "substitute for otherwise costly acquisition of private information." See also Diamond (1985).

By happenstance, two earlier papers demonstrate that management forecasts are not always more accurate than analysts' forecasts. The first was Williams (1996), who examines the *usefulness* of management forecasts (defined by whether the management forecast moves earnings expectations in the direction of realized earnings) and the resulting response to these forecasts by analysts. Williams does not report descriptive statistics that allows one to infer the frequency with which management's forecasts are more accurate than the prevailing analyst consensus forecasts. However, Hutton and Stocken (2010) document that for their sample of 6,655 quarterly and annual management forecasts, managers are more accurate than the prevailing consensus analyst forecast only about 50 percent of the time.

This observation begs the question: *When are analysts' forecasts more accurate than management's forecasts, given the inside information managers possess?* We scower the extant analyst forecast literature and management guidance literature to develop conjectures about when analysts have an information advantage over management and thus when analysts' forecasts are likely to be more accurate than management's forecasts.

Our review of the literatures suggests that analysts' information advantage stems from three sources: their ability to be objective when top executive are likely to be overconfident, their abilities as industry specialists, and finally their access to experts in macroeconomics. When firm fortunes move with broad macroeconomic factors and depend on forces outside management's control (e.g., cyclical, input prices, regulation and competition), analysts are better positioned to create a distinctive information advantage via their acquisition of private information. For these firms, management's forecasts are *not* a close substitute for analysts' costly acquisition of private information.

Prior literature also points out when analysts' forecasting abilities are inadequate. For instance, they appear to be less able to forecast earnings for firms with high fixed costs, firms with abnormally high inventory growth, and complex firms that provide opaque disclosures, giving management the advantage in these situations. We go one step further with these arguments and suggest below that management has an information advantage over analysts when management holds the decision rights that affect the resulting earnings.

Management's Information Advantage

Managers are **Firm Specialists**, who have an *information advantage* because they run the firm making business decisions hourly and daily that ultimately affect reported earnings. Because they have intimate knowledge of the firm's business transactions, managers are entrusted with making the appropriate estimates and assumptions needed to prepare accrual-based financial statements. Early research exploring the usefulness of management earnings forecasts documents that analysts' forecast errors decrease more rapidly for firms that release management earnings forecasts than for firms that do not (Hassell, Jennings and Lasser 1988). This is not surprising, given that management makes key decisions regarding the timing and recognized amounts of business transactions. These accounting decision rights give management a clear information advantage in forecasting earnings, especially near-term earnings. Thus, we expect management forecasts to be more accurate than analysts' forecasts the shorter the horizon of the forecast. In fact, Baginski and Hassell (1990) find that analysts revise their forecasts to fall more in line with management's forecasts in the fourth quarter.

The unique information advantage that results from management holding key decision rights is likely to be most pronounced when the firm's current situation is unusual, for example in a loss year. Loss years are by their very nature off-equilibrium years, years when the firm is not operating within its band of steady state performance which makes forecasting earnings based on historical performance particularly difficult. In loss years, management's inherent information advantage is enhanced by the difficulty outsiders face in anticipating what management is likely to do in response to the crisis. Without knowing management's likely actions, it is exceedingly difficult to forecast the implications of those actions for reported earnings. This disadvantage is particularly acute at the beginning of the fiscal year, before management has had a chance to communicate to outsiders its plans for dealing with the crisis. Thus, we also expect managers to provide more accurate forecasts than analysts when management is forecasting a loss for the year.[2]

Continuing to highlight circumstances when management's distinctive information advantage as insiders running the firm is likely to be most pronounced, we expect management's forecast to be more accurate than analysts' forecasts when the firm is experiencing abnormally high inventory buildup and when a firm with high fixed costs experiences a significant decline in its revenues (i.e., when the firm has excess capacity).

Recent research documents shortcomings in analysts' forecasting abilities in these two situations. For instance, Kesavan and Mani (2010) document the predictive power of abnormal inventory growth for retail firms' earnings and that analysts' forecasts fail to incorporate this relevant information. We simply add to their arguements that management is in a better position to understand how abnormal inventory growth is likely to affect the firms' operating performance precisely because management is either directing the growth in anticipation of increased demand or is active in addressing it with impending markdowns or write-offs, the timing of which management controls.

Similarly, Weiss (2010) documents that analysts' forecasts are less accurate for firms with more sticky costs. A firm with more sticky costs, when faced with a decline in demand, is

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[2] Loss years often involved the recognition of special, non-recurring items, exactly the types of accounting items whose timing and magnitudes depend on key estimates and assumptions made by management, giving them a clear advantage in forecasting earnings. However, the earnings construct forecast by analysts and management often exclude non-recurring special times.

more likely to experience excess capacity. Since management has intimate knowledge of its plans to address the excess capacity, we conjecture that management forecasts will be more accurate than analysts' forecasts when a firm's costs are more fixed and the firm experiences a decline in revenues.

Analysts' Information Advantage

Given management's distinctive information advantage as insiders running the firm, what are the possible sources of analysts' information advantage? We argue that there are several.

First, analysts as outsiders are likely to be more *objective* in evaluating the economic consequences of firm's investment, operating and financing decisions. Overconfidence, defined by Schrand and Zechman (2010, p.2) "as a cognitive trait, which in the context of a corporate manager, results in unrealistic (positive) beliefs about future firm performance" is a prevalent characteristic of top executives.[3] Executive overconfidence ought to lead to inflated earnings expectations and optimistic forecasts, especially early in the fiscal year. If analysts are able to be more objective, their forecast errors ought to smaller (and less optimistically biased).[4]

Second, as outsiders studying the competitive landscape of an industry, analysts are in a better position to assess in an objective manner the competitive positioning of a particular firm within its industry and the sustainability of its position. Analysts are **Industry Specialists**. Financial institutions commonly organize analysts by industry and sector and analysts routinely benchmark a firm's performance against its direct competitors (see Ramnath 2002). Clement (1999) and Jacob et al. (1999) show that analysts' forecast accuracy improves with industry

[3] See Englmaier (2004), Heaton (2002) and Schultz and Zaman (2001), for surveys of the evidence. Research documents an association between managerial overconfidence and distorted corporate investment, financing and financial reporting decisions (e.g., Malmendier and Tate, 2005; Ben-David, Graham and Harvey, 2007; Melmendier, Tate and Yan, 2007; Hirshleifer, Low and Teoh, 2010; Hribar and Yang, 2010; Schrand and Zechman, 2010).

[4] We intend to examine whether management's long-horizon forecasts are more optimistically biased than analysts' long-horizon forecasts in future drafts of this paper.

specialization, while Gilson et al. (2001) show that the composition of analyst coverage changes after spin-offs and equity carve-outs. Finally, Boni and Womack (2006) demonstrate that analysts' expertise lies in their ability to rank stocks *within* the industries in which they specialize.[5] Together, these results suggest that analysts' comparative advantage lies in interpreting specific industry and market sector trends and improving intra-industry information transfers.

Third, analysts have access to macroeconomic expertise that affords them a distinctive information advantage in predicting economy-wide factors that lie outside management's control (such as GDP, interest rates, and energy costs) and understanding their implications for industry-level and firm-level performance. Specifically, analysts working at top tier investment banks have proprietary access to highly regarded macroeconomists (Jennings 1987). The morning conference calls taking place each day at these banks alert analysts to any forthcoming macroeconomic news and its implications.[6] Additionally, these macroeconomists provide analysts with detailed forecasts of commodity prices and interest rates, which ought to be useful for predicting the performance of many regulated firms: e.g., utilities whose profits depend on energy costs and commercial banks whose profits depend on the shape of the yield curve. As a specific example, the *Economic Research Group* at Goldman Saches **"**formulates macroeconomic forecasts for economic activity, foreign exchange rates and interest rates based on the globally coordinated views of its global and regional economists."[7] These are precisely the factors affecting firm operations that lie outside management's influence. The amount of

[5] Consistent with this view, Boni and Womack implement a simple trading strategy wherein *within* each industry they buy firms with net upgrades by analysts and sell short firms with net downgrades by analysts and document that this *within* industry strategy generates on average a 30% higher returns than a similar non-industry approach.
[6] In contrast, managerial earnings guidance has been shown to *lag* macroeconomic news (see Anilowski, Feng and Skinner, 2007).
[7] http://www2.goldmansachs.com/services/research/gir/research-and-analysis.html.

resources devoted to macroeconomic research by these investment banks are significant, and any individual operating firm is unlikely to have access to the same level of resources and expertise.

Empirical evidence supports these conjectures: Piotroski and Roulstone (2004) find that stock return synchronicity is positively associated with analyst forecasting activities, consistent with analysts increasing the amount of *industry* and *market-level* information in prices. Conversely, they find that stock return synchronicity is negatively related to greater levels of insider trading, indicating that the net contribution of managers' trading activities is to increase the relative amount of *firm-specific* information in stock prices.

3. **Sample selection and Variable definitions**

We use the *First Call* database of "Company Issued Guidance" (*CIG)* to identify a sample of 31,279 annual management earnings forecasts issued between January 2001 and December 2007. Our sample period begins after the passage of Regulation Fair Disclosure (RegFD). Prior to RegFD, managers could leak their forecasts privately to analysts, making our analysis of the relative accuracy of the earnings forecasts by these two groups difficult.[8] We exclude qualitative forecasts not specific enough to provide numerical earnings per share (EPS) forecasts needed to construct measures of forecast accuracy. In addition, we exclude observations with missing realized earnings on *First Call*.

We then merged our *First Call* sample with the *I/B/E/S* detailed file of individual analyst earnings estimates and with the *I/B/E/S* actual earnings. We conduct our main analysis on the first annual management earnings forecast issued after the release of the prior year's earnings.

[8] The regulatory and legal environment affects management forecasting behavior (see Baginski, Hassell and Kimbrough 2002). To control for these effects, we restrict our sample to forecasts issued after the implementation of Reg FD on October 23, 2000. Early evidence suggests that Reg FD affects voluntary disclosure practices (Heflin, Subramanyam and Zhang 2003).

We expect that the relative accuracy of analysts and managers early in the year is driven by their comparative information advantage; late in the fiscal year management ought to have a clear advantage in meeting their forecasts via earnings manipulation (see Kasznik 1999). We delete management forecasts that are not the first annual forecasts issued after the prior year's earnings announcement (13,704) and those that are the first annual forecasts but issued in the fourth quarter (79).

For each management forecast, we gather all earnings forecasts for the same fiscal year made by individual analysts within the previous 30 days to ensure that the analyst forecasts used in our analysis are not stale.[9] The timeline of management forecasts and the corresponding analyst forecasts is presented in Figure 1. Management forecasts that do not have any corresponding I/B/E/S analyst forecasts made within the 30 day window are deleted (11,976). If a management forecast is made *within* 30 days after the prior year's earnings announcement, we adjust the window for gathering analyst forecasts to start two days after the prior year's earnings announcement. This adjustment ensures that the analysts have also observed the prior year's earnings.[10]

Since we use data from both I/B/E/S and CIG, it is important to ensure the consistency of the earnings construct being forecast by analysts and managers. We compare the actual EPS values on CIG and on I/B/E/S, and delete observations where the two are not equal (986). Finally, we merge the sample of *First Call* earnings forecasts with financial data from *Compustat,* and delete observations with missing *Compustat* data (1,028). The sample

[9] For our primary set of tests we give management the advantage, in that management's forecast is made after the analysts' forecasts. In future drafts we plan to reverse the advantage and compare the relative accuracy of analysts' forecasts made after management's forecasts.
[10] A total of 119 management forecasts have less than 3 corresponding analyst forecasts available during this shorter window and are deleted.

development is summarized in Table 1. The final sample consists of 3,387 management forecasts.

Variable Definitions: Analysts' Information Advantage

As discussed earlier, analysts' information advantage in predicting firm-level earnings comes from their expertise as industry specialists and from their access to experts in macroeconomic forecasting. Thus, we expect analysts' forecasts to be more accurate than management's when the firm's fortunes move with the broad economy and with their industries.

To capture the extent to which a firm's earnings move with the broad economy, we compute *Cyclicality* a measure that captures the ability of Gross Domestic Product (GDP) to explain firm-level earnings. Specifically, for each firm-year observation, we regress the firm's quarterly earnings over the prior 12 quarters on the corresponding quarterly Gross Domestic Product:

$$EARN_{i,t} = \alpha_0 + \alpha_1\, GDP_t + \varepsilon_{i,t}$$

where *EARN* is defined as income before extraordinary item and *GDP* is the nominal quarterly Gross Domestic Product. We define *Cyclicality* as the coefficient of determination (R^2) from the estimation of the above regression. A high *Cyclicality* value indicates that the variability of a firm's earnings is well explained by variability in overall economic activity (positively or negatively), suggesting that analysts ought to have an information advantage over management, since they have access to experts who provide detailed forecasts of macroeconomic conditions. Thus, we expect analyst forecasts to be more accurate when a firm's *Cyclicality* measure is high.

Appendix 2 reports the mean and median *Cyclicality* across the Fama and French (1997) 48 industries. There is substantial variation in the *Cyclicality* measure across the 48 industries. The two industries that have the lowest mean *Cyclicality* are Tobacco Products and Candy and

Soda. The five industries that have the highest mean *Cyclicality* are Aircraft, Construction, Defense, Healthcare, and Shipbuilding and Railroad. This is consistent with our intuition. For example, Construction is a classic cyclical industry; 'housing starts' varies substantially with the state of the economy.

We argue that analysts are industry experts highly capable of forecasting and interpretation of industry demand and dynamics. We expect this expertise to translate into an information advantage for analysts when forecasting earnings for firms whose product demand moves in synch with its industry. To identify firms for which this analyst information advantage is likely, we compute a *Revenue Synchronicity* measure that captures how a firm's sales growth is correlated with the underlying industry growth. Specifically, *Rev Sync* is measured as the R^2 from the firm-level estimation of the model over the prior 12 quarters:

$$\textit{Sales Growth}_{i,t} = \alpha_0 + \alpha_1 \textit{ INDSALE Growth}_t + \varepsilon_{i,t}$$

where *Sales Growth* is defined as the percentage change in revenue from the prior quarter. *INDSALE Growth* is the percentage change in the aggregate industry revenues. The industry classification is based on Fama and French (1997).

We focus on *Sales Growth* because existing evidence suggests that analysts' information advantage as industry specialists provides them with an enhanced ability to forecast sales growth, but not necessarily bottom line profits. First, there is a stronger correlation between firm sales and industry sales than between firm profits and industry profits (see Givoly, Hayn and D'Souza 1999, table 2 on page 25). Second, Fairfield, Ramnath and Yohn (2009) observe that industry-specific models generate more accurate forecasts of firms' sales growth than economy-wide models, but not so for firm-level profitability. They argue that their findings are not surprising since "firms' sales growth depends on changes in product demand, which are generally determined at the industry level." Further, the superiority of industry-specific models in predicting revenue growth, but not profitability, is consistent with the existence of sustainable differences in cost structures across firms within the same industry (Weiss 2010; Givoly, Hayn and D'Souza 1999). If analysts have an information advantage over managers in forecasting industry level demand shocks, then we expect analysts' forecasts to be more accurate when a firm's sales growth is highly synchronous with its industry.

Firms in regulated industries face common constraints, and the resulting commonality among the firms likely benefits analysts' private information acquisition. In addition, the performance of regulated firms tends to depend on input prices forecast by macroeconomists working with sell-side analysts at top tier investment banks. For example, financial institutions' profits often depend on the shape of the yield curve, while utilities' profits depend on the costs of their main inputs, energy prices. If analysts enjoy an information advantage afforded them by macroeconomists' detailed forecasts of energy costs and interest rates, then their forecasts for regulated firms are likely to be more accurate than those of management. Consistent with the prior literature, we define *Regulated* industries as financial institutions and utilities. Specifically, we define a dummy variable, equal to one if a firm's four-digit SIC code fall between 4900-4999 (utilities), 6000-6099, 6100-6199 (banking), and 6200-6299, 6700-6799 (financial institutions), and zero otherwise.

Variable Definitions: Managers' Information Advantage

Managers have an information advantage because they run the firm and make key business decisions that ultimately affect reported earnings. As discussed earlier, the information advantage that results from management holding key decision rights is likely to be most pronounced when the firm's current situation is unusual, making it particularly difficult for analysts to anticipate the actions managers will take and the implications of these actions for reported earnings. Specifically, uncertainties regarding possible managerial actions are likely to arise in loss year, in years when the firm has a buildup of excessive inventory, and in years when the firm has excess capacity.

We define a firm year as a *Loss* year when the EPS forecast by management is negative; we expect managers to provide more accurate forecasts than analysts in these years. Identifying firms with excess inventory buildup is done in five steps: (1) we compute for each firm-year days inventory, where days inventory is equal to (inventory /cost of goods sold) * 365; (2) we compute the average days inventory for each industry-year, where the industry classification is again based on the Fama and French (1997) industry groupings; (3) we compute a normalized deviation from the industry average days inventory, measured as (DI_{it} – Industry mean DI_t) /Industry standard deviation of DI_t; (4) we isolate firm-years where inventory is a significant asset class, defining *High Inventory* as the subsample of firm-years ranking in the top tercile of the ratio of inventory to assets; (5) we identify high abnormal inventory (*High ABI)* as the firms falling in the top tercile of the normalized deviation from the industry average days inventory. Since we expect management's information advantage to be most pronounced for the subset of high inventory firms experiencing abnormal high inventory buildup, we interact the latter two variables in our regression analysis presented below.

To identify firm-years with excess capacity, we are interested in identifying firms facing high fixed costs that are also experiencing a significant decline in demand. Such firm-years are expected to pose a forecasting challenge for analysts as it is uncertain how management will respond to the excess capacity and how their response will affect reported earnings. To identify firm-years with excess capaticy, we first measure a firm's *Cost Structure*, by estimating the following firm-level regression using data from the prior 12 quarters (similar to Anderson et al., 2003):

$$LOG(EXP_t / EXP_{t-1}) = \beta_0 + \beta_1 LOG(REV_t / REV_{t-1}) + \varepsilon_{i,t}$$

where *REV* is defined as revenue and *EXP* is defined as revenue minus income before extraordinary item. A high value of β_1 means that a firm's costs are sensitive to its revenue, suggesting that the costs are mostly variable. Conversely, a low value of β_1 means that a firm's costs do not vary much with the revenue, meaning they are sticky (fixed). We then obtain industry-adjusted cost structure measure by subtracting the industry average in that year from our firm-year measure. Firms with relatively high fixed costs (those in the bottom tercile of the industry adjusted cost structure measure) are more likely to experience excess capacity when there is a decline in product demand, shifting the information advantage to managers. We use revenue volatility to proxy for the probability of a demand drop.[11] Revenue volatility (*Std Rev*) is the standard deviation of the revenue over the prior 12 quarters, scaled by the average revenue over the same period. To capture the interactive effect of cost structure and a decline in demand, we interact the *High Fixed Cost* dummy variable with the *High Std Rev* dummy variable (those in the top tercile). Assuming managers know how they plan to deal with the excess capacity and the consequences for reported earnings, we expect that high fixed costs, coupled with a decline in demand, increases managers' informaiton advantage over analysts.

[11] We use the standard deviation of revenue over the prior 12 quarters as our proxy for the probability of a demand drop, rather than an actual decrease in revenues in the current fiscal year. We do so because we want all of our independent variables to be determined prior to the issuance of the analyst and management forecasts used in our analyses. Identifying firms using actual revenue decreases in the current fiscal year would introduce a peek-ahead bias. We want our variables to be observable ex ante so that investors can use our analysis to inform the relative weights they place on analyst and management forecasts when forming their own earnings expectations. However, we recognize that our proxy for the probability of a demand drop (*High Std Rev*) is imperfect and introduces noise into the empirical analysis.

Finally, we expect management to have a forecasting advantage over analysts for shorter horizon forecasts. First, analysts' information advantages in forecasting macroeconomics variables and industry demand shocks are likely to dissipate as the forecast horizon shortens and the end of the fiscal year approaches. This is because later in the fiscal year many of the macro- and industry-level shocks would have been observed by managers. Second, managers have the ability and incentives to manage earnings toward their own forecasts (Kasznik, 1999). We expect their manipulation efforts to be more successful with short horizon forecasts. Thus, we expect management's information advantage over analysts to be greater when the horizon between the management forecast date and the end of the fiscal year is shorter. We measure *Horizon* as the number of days between the date of the management earnings forecast and the end of the fiscal year.

Control Variables

We control for a number of variables that are related to a firm's general information environment, and therefore likely to affect forecast accuracy in general as well as the relative accuracy of management's and analysts' forecasts. However, we do not predict the signs of the control variables, as for most the effect on the relative accuracy of management and analyst forecasts is unclear to us.

Prior work finds that firm *Size* is an important determinant of analyst following (Lang and Lundholm 1996; Barth, Kasznik and McNichols, 2001). Larger firms tend to have better information environments but potentially more complex operations, both of these are likely to affect forecast accuracy. We measure firm *Size* as the natural logarithm of total assets, measured at the end of the prior fiscal year.

We also control for a firm's market to book ratio, *MB*, measured as the market value of equity divided by the book value of equity. Firm with high market to book ratios are likely to have more growth opportunities. High-growth firms tend to attract greater analyst following due to greater visibility, but analysts are also expected to have greater difficulty in accurately forecasting earnings for high growth firms (Barth et al., 2001).

Leverage can also affect the information environment of a firm. For firms with more debt, the scrutiny and monitoring by debt holders potentially improves the firm's information environment. *Leverage* is measured as total assets divided by book value of equity.

We also expect the number of analysts following a firm to affect our measure of relative accuracy of management and analyst forecasts. Assuming individual analysts' information sets are not perfectly correlated, averaging across a greater number of analysts' forecasts will provide a mean analyst forecast that is less noisy and more accurate.[12] *Analyst Following* is measured as the natural logarithm of the number of analyst forecasts issued within the thirty days prior to the management forecast.

We also control for a firm's overall complexity and forecasting difficulty using the *Dispersion* of analyst forecasts and the *Fog Index* (Li, 2008). Greater forecast dispersion reflects the general difficulty in forecasting earnings for a specific firm. *Dispersion* is measured as the

[12] By the same token, one could argue that our research design inherently biases in favor of analysts by comparing the *average* forecast across *N* analysts to a *single* management earnings forecast. However, this would only be true if the management forecast is drawn from the same distribution as all the individual analyst forecasts. As we argue in the paper, management's information set is distinct from that of analysts, meaning that it is unlikely that the management forecast is drawn from the same distribution as the individual analyst forecasts. Specifically, the management forecast is likely to be drawn from a distribution with a smaller variance due to the manager's role as the "insider" running the firm. In addition, our research design gives the manager an inherent "advantage" because the management forecast is issued *after* management observes the *N* analyst forecasts. So the management forecast is not based on a single observation, but rather on a total of *N* analyst forecasts plus the manager's own information set. For these reasons, we do not believe that our research design inherently biases in favor of analyst accuracy. Nevertheless, we control for the number of analysts in the cross sectional regression analysis.

standard deviation of the consensus analysts forecast scaled by the mean consensus analyst forecast, both measured in the month prior to the issuance of the management forecast. We also use the *Fog Index* as developed by Li (2008) as a control variable.[13] This measure captures the readability of the firm's prior period's 10-K filings, and is a comprehensive measure of the firm's overall complexity. Lehavy, Li and Merkley (2010) document that a higher *Fog Index* is associated with lower analyst forecast accuracy.

We also control for the structure of industry. The more concentrated an industry is, the more likely the performance of its members are inter-related, which suggests that analysts ought to have an information advantage, if they are better at objectively assessing the overall industry and the individual performance of its members. However, managers in concentrated industries are also more vested in learning about their competitors, making the relative information advantage between the two hard to predict. We measure industry concentration using the *Herfindahl Index*, defined as $\sum_{i=1}^{N} MKTSHARE_i^2$ where *MKTSHARE* is the market share for each firm in the industry. Market share for firm i is measured as the revenue for firm i divided by total revenue for all firms in the industry, again classified based on Fama and French (1997).

4. **Empirical Results**

Table 2 provides descriptive statistics for the 3,387 management earnings forecasts. Since we focus on the first annual forecast, the horizon of the management forecasts measured relatively to the end of the fiscal year is relatively long, with an average of 210 days, and a median of 244 days. Consistent with the existing literature, management earnings forecasts tend

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[13] We are grateful to Feng Li for generously providing us with the data on the *Fog Index*.

to be issued by large firms, the sample firms have an average total asset of $4.87 billion dollars and a median of $1.23 billion dollars.

In Table 3, we provide descriptive statistics for two subsamples: those where management forecasts are more accurate and those where the mean analyst forecasts are more accurate. We define a management forecast as being more accurate if the absolute value of the management forecast error (measured as realized earnings per share less the management forecast of earnings) is smaller than the absolute value of the mean forecast error of the analyst forecasts (measured as realized earnings per share less the corresponding mean analyst forecasts), that is,

$$|\text{Mean Analyst Estimate} - \text{Realized EPS}| > |\text{Management Forecast} - \text{Realized EPS}|.$$

As seen in Table 3, management forecasts in our sample are more accurate than the mean analyst forecast slightly less than 50% of the time (1,658 out of 3,387), consistent with the finding in Hutton and Stocken (2010). Comparing the two subsamples, many of the firm characteristics of interest differ as predicted. Specifically, the sample of firms where the mean analyst forecasts are more accurate exhibit greater *Cyclicality*; the difference in cyclicality between the two subsamples is highly significant. These firms also exhibit greater *Revenue Synchronicity* with their industry sales growth, as a greater proportion fall into the high revenue synchronicity (*High Rev Sync*) category compared to the proportion for the subsample where management's forecasts are more accurate. The difference in proportions is significant at the 10% level using 2-tailed tests. In addition, for the subsample of firms where the mean analyst forecasts are more accurate, there is a higher fraction of firms in *Regulated* industries. Finally, for the subsample where the mean analyst forecasts are more accurate, the corresponding management forecasts have a longer *Horizon* measured relative to the end of the fiscal year;

again the difference is highly statistically significant. These univariate results are consistent with our conjectures that analysts' information advantage resides at the macro- and industry-level, and when the forecast horizon is relatively long.

For the subsample of firms where managers' forecasts are more accurate, they are more likely to be *Loss* years, and firm-years with *High Inventory*. As for the control variables, they tend to be statistically indifferent between the two subsamples.

Table 4 provides the correlations among our variables of interest and all the control variables. The table reports Pearson correlation on the upper diagonal and the Spearman correlation on the lower diagonal. While many of the variables are significantly correlated, the magnitude of the correlation does not raise significant concerns of multi-collinearity for our variables of interest. Only a few control variables are correlated at levels greater than 30%.

While the univariate results are consistent with our empirical predictions, we perform regression analysis to ensure that our main inferences are robust to the inclusion of the control variables discussed earlier. The regression results are presented in Table 5. The dependent variable is set to one if the management forecast is more accurate than the average of the prevailing, non-stale analysts' forecasts, and zero otherwise. We present the predicted signs of the coefficients for our variables of interest, the coefficient estimates, and the Z-statistics. The standard errors are clustered by firm. The magnitude and the standard error of the interaction terms are estimated based on Ai and Norton (2003). For ease of interpretation, we also present the marginal impact of each variable. The marginal impact is the expected change in the probability of a more accurate management forecast resulting from an increase in the independent variable from the 25^{th} to the 75^{th} percentile of the sample distribution when the independent variable is continuous, and from 0 to 1 if it is an indicator variable, holding all other independent variables at their means.

Table 5 reveals that the relative accuracy of management and analyst forecasts is predictably related to our variables of interest, both variables meant to identify analysts' information advantage as well as those meant to identify management's information advantage. Specifically, the coefficients on *Cyclicality*, *High Rev Sync*, *Regulated* and *Horizon* are all negative and significant, indicating that analysts have an information advantage (i.e. managers are less accurate) when a firm's fortunes move with the broad economy, when its sales growth is highly synchronous with its industry, when the firm is either a utility or financial services institution, and when the managerial earnings forecast is issued earlier in the year.

Also consistent with our predictions, managers are more accurate than analysts when it is harder for analysts to anticipate managements' actions. Specifically, the interaction between *High Fixed Costs* and *High Std Rev* is positive and significant, suggesting that managers have an information advantage when firms have excess capacity.[14] Unable to anticipate exactly how managers will respond to the change in product demand, it is difficult for analysts to anticipate the effects of high fixed costs and highly variable revenues on reported earnings.[15]

In addition, the coefficient on *Loss* is positive and significant, suggesting that managers are more accurate when they are anticipating a loss. As insiders running the firm, management

[14] We focus on excess capacity versus demand in excess of existing capacity, as firms with high fixed costs are not able to respond quickly to dramatic increases in demand, since such a response is more long-run requiring the building of new production capacity. On the other hand, when demand drops for firms facing high fixed costs, reported earnings are likely to be dramatically affected by management's near-term decisions. Management will either find ways to utilize the excess capacity, presumably by decreasing prices to increase demand, which could either increase or decrease reported earnings. Alternatively, management may allow revenues and earnings to drop, without decreasing prices in the hope that the demand shock is temporary.

[15] Interestingly, the positive correlation (= 0.188) in Table 4 between the *Loss* indicator variable and the excess capacity indicator variable (*High Fixed Cost* * *High Std Rev*) is evidence that often times such an operating situation results in a loss for the fiscal year.

knows its plans for addressing the underlying reasons for the loss and presumably the implications of its plans for reported earnings.

Finally, the coefficient on the interaction between *High Inventory* and high abnormal inventory (*High ABI)* is positive and significant. This suggests that for firms where inventory is a significant asset class, excess inventory buildup results in an information advantage for managers. Management has either been building the inventory in anticipation of increased demand or will decide how to deal with the excess inventory through markdowns or write-offs. Management knows it plans and can anticipate better the likely effect on reported earnings.

Examining the coefficients on the control variables none are significant. In particular, analyst forecast *Dispersion* and the *Fog Index*, which proxy for difficulty forecasting earnings and firm complexity, are not significant. Industry structure, measured using the *Herfindahl* index, is also insignificant.

Overall, inferences based on the regression analysis are consistent with the univariate results: Analysts appear to have an information advantage at the macro- and industry-level, while managers have an information advantage because they hold key decision rights, and their relative advantage is enhanced in situations where analysts find it difficult to anticipate managers' actions and the resulting implications for reported earnings.

Additional Robustness Checks

Alternative Industry Classifications

We perform our main analysis using Fama and French (1997) 48 industries. However, prior research indicates that alternative methods of industry classification can significantly affect tests of industry influences (Bhojraj, Lee, and Oler, 2003). Because we argue that analysts have an information advantage at the industry level, it is important that the industry classifications we use capture analysts' industry specializations. To check the robustness of our findings to alternative industry classifications, we repeat our main analysis using the Global Industry Classification Standard (GICS) to classify industry groupings. The untabulated results are very similar; all of main inferences remain unchanged.

Alternative Proxies

Instead of using the *Fog Index* to proxy for firm complexity, we also use two other proxies based on prior literature. The first is a measure of the amount of intangibles in a firm. Consistent with Barth et al. (2001), we measure intangibles as the ratios of research and development expense and advertising expense to total operating expenses for a given year, less the respective industry average ratio for that year. The second measure uses segment data to calculate firm level diversification as a measure of complexity. Neither of these alternative measures of firm complexity is significant, and our main findings are unaffected when these alternative measures are included in the regression analysis.

5. Conclusion

To our knowledge, we are the first to examine the relative accuracy of management and analyst forecasts and to document the firm characteristics and operating situations associated with analysts providing more or less accurate annual earnings forecasts than management. Our strongest finding is that analysts' forecasts are more accurate than management's when a firm's fortunes move in concert with broad macroeconomic and industry-level factors. This includes not only cyclical firms, but also regulated firms whose performance depends on such macro factors as interest rates and energy prices.

In contrast, management's forecasts are more accurate when the firm is experiencing unusual circumstances, such as a loss, abnormal inventory buildup, or excess capacity. In these situations, management's near-term decisions undertaken in response to the unusual circumstance greatly affect reported earnings. Thus, analysts are at a disadvantage because it is difficult for them to anticipate how management will respond to the unusal situation and even more difficult for them to assess the effect of management's response on reported earnings.

To our knowledge, we are also the first to highlight and investigate the fact that management's forecasts are more accurate than analysts' forecasts only about 50% of the time. By doing so we rebuff the premise in the literature that management has an information advantage over analysts that permits its earnings guidance to substitute for the private information acquired by analysts (Diamond 1985, Altschuler 2009). Analysts bring something unique to the table, an ability to incorporate in a sophisticated and objective manner macro-level and industry-level information into firm-level earnings forecasts. Thus, our empirical evidence ought to be useful to investors when forming their own earnings expectations; it suggests putting more weight on analysts' forecasts for cyclical firms, regulated firms and firms with greater industry-based revenue synchornicity. On the other hand, investors should put more weight on management's forecasts when the firm is facing unusual circumstances, such as a loss, abnormal inventory buildup or excess capacity.

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TABLE 1
Sample Selection

	No. of Forecasts
First Call CIG dataset of annual earnings per share forecasts, January 2001 through December 2007	31,279
Less:	
Firms that do not have any I/B/E/S analysts' forecasts 30 days before the management forecast	11,976
Management forecasts that are not the first forecast made after last period's earnings announcement	13,704
Firms that have management forecasts that are made less than 30 days from the last period's earnings announcement and have less than 3 analyst forecasts that are made after last period's earnings announcement	119
Management forecasts announced in the last quarter of the year	79
Actual value of EPS on CIG is not equal to actual value of EPS reported on I/B/E/S	986
Missing data for variables used in the regression	1,028
FINAL	**3,387**

Note to Table 1:
Figure 1 presents a diagram showing the timing of the management and analyst forecasts used in our sample.

TABLE 2
Descriptive statistics for the entire sample: 3,387 firm-year observations, 2001 to 2007

Variable	N	Mean	Std dev	25%	Median	75%
CYCLICALITY	3387	0.292	0.274	0.053	0.205	0.469
REVENUE SYNCHRONICITY (REVSYNC)	3387	0.237	0.252	0.033	0.143	0.380
HIGH REV SYNC (0/1)	3387	0.500	0.500	0.000	1.000	1.000
REGULATED (0/1)	3387	0.082	0.274	0.000	0.000	0.000
COST STRUCTURE	3387	0.001	0.513	-0.118	0.006	0.139
HIGH FIXED COSTS (0/1)	3387	0.333	0.471	0.000	0.000	1.000
REVENUE VOLATILITY (STD REV)	3387	0.201	0.147	0.099	0.157	0.260
HIGH STD REV (0/1)	3387	0.333	0.471	0.000	0.000	1.000
*HIGH FIXED COSTS * HIGH STD REV (0/1)*	3387	0.117	0.321	0.000	0.000	0.000
LOSS (0/1)	3387	0.024	0.154	0.000	0.000	0.000
INVENTORY	3387	0.116	0.148	0.007	0.073	0.162
HIGH INVENTORY (0/1)	3387	0.318	0.466	0.000	0.000	1.000
ABNORMAL INVENTORY (ABI)	3387	-0.054	0.608	-0.245	-0.100	-0.011
HIGH ABI (0/1)	3387	0.318	0.466	0.000	0.000	1.000
*HIGH INVENTORY * HIGH ABI (0/1)*	3387	0.158	0.365	0.000	0.000	0.000
HORIZON	3387	210	65	160	244	253
TOTAL ASSETS	3387	4870	10372	428	1233	3780
SIZE = LN(ASSETS)	3387	7.215	1.587	6.059	7.117	8.218
MB	3387	3.380	3.515	1.701	2.542	4.006
LEVERAGE	3387	2.676	2.310	1.525	2.085	2.925
ANALYST	3387	4.348	4.279	1.000	3.000	6.000
ANALYST FOLLOWING=LN(ANALYST)	3387	1.079	0.870	0.000	1.099	1.792
DISPERSION	3387	0.045	0.079	0.014	0.025	0.048
FOG INDEX	3387	19.585	1.663	18.484	19.370	20.382
HERFINDAHL	3387	0.053	0.052	0.032	0.040	0.056

Notes to Table 1:
All variables are defined in Appendix 1. Indicator variables are identified with a (0/1) after the names. All continuous variables are winsorized at the extreme 1%.

TABLE 3
Descriptive statistics splitting firm-year observations based on whether management or analyst forecasts are more accurate (smaller absolute forecast error)

Variable	Management forecasts are more accurate (1)	Analyst forecasts are more accurate (2)	(1) – (2)	Predicted Sign
No. of observations	1,658	1,729		
CYCLICALITY	0.274	0.308	-0.033***	-
REVENUE SYNCHRONICITY (REV SYNC)	0.234	0.239	-0.005	-
HIGH REV SYNC (0/1)	0.484	0.516	-0.032*	-
REGULATED (0/1)	0.075	0.088	-0.014*	-
COST STRUCTURE	0.000	-0.005	0.006	+/-
HIGH FIXED COSTS (0/1)	0.332	0.335	-0.003	+/-
REVENUE VOLATILITY (STDREV)	0.200	0.202	-0.002	+/-
HIGH STD REV (0/1)	0.326	0.340	-0.014	+/-
*HIGH FIXED COSTS * HIGH STD REV (0/1)*	0.121	0.113	0.008	+
LOSS (0/1)	0.028	0.020	0.008*	+
INVENTORY	0.122	0.111	0.010**	+/-
HIGH INVENTORY (0/1)	0.324	0.312	0.012*	+/-
ABNORMAL INVENTORY (ABI)	-0.059	-0.049	-0.010	+/-
HIGH ABI (01/)	0.324	0.313	0.011	+/-
*HIGH INVENTORY * HIGH ABI (0/1)*	0.162	0.155	0.007	+
HORIZON	207	214	-7***	-
TOTAL ASSETS	4995	4750	245	+/-
SIZE = LN(ASSETS)	7.197	7.233	-0.036	+/-
MB	3.291	3.466	-0.175	+/-
LEVERAGE	2.694	2.658	0.035	+/-
ANALYST	4.409	4.289	0.120	+/-
ANALYST FOLLOWING =LN(ANALYST)	1.081	1.077	0.004	+/-
DISPERSION	0.047	0.043	0.003	+
FOG INDEX	19.567	19.603	-0.036	+
HERFINDAHL	0.055	0.059	-0.005	+/-
MFERROR	0.167	0.196	-0.029	-
AFERROR	0.215	0.136	0.079***	+

Notes to Table 3
All variables are defined in Appendix 1. Indicator variables are identified with a (0/1) after the names. All continuous variables are winsorized at the extreme 1%. *, ** and *** represent significance at 10%, 5% and 1% respectively (2-tailed). In the column (1)-(2), we test the differences in means of continuous variables using the t-test and the differences in proportions of indicator variables using the chi-square test.

TABLE 4
Correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1.CYCLICALITY		-0.001	-0.071	-0.052	0.025	-0.006	0.027	0.024	-0.054	0.004	0.009	-0.083	0.100	-0.045	0.024	-0.061	0.051	0.069
		(0.934)	(0.000)	(0.002)	(0.138)	(0.713)	(0.116)	(0.160)	(0.002)	(0.820)	(0.610)	(0.000)	(0.000)	(0.009)	(0.172)	(0.000)	(0.003)	(0.000)
2.HIGH REV SYNC	0.005		-0.049	-0.021	-0.096	-0.068	-0.035	0.092	0.012	0.055	0.103	0.074	0.036	0.002	0.070	-0.028	-0.028	0.031
	(0.761)		(0.005)	(0.225)	(0.000)	(0.000)	(0.044)	(0.000)	(0.469)	(0.001)	(0.000)	(0.000)	(0.037)	(0.897)	(0.000)	(0.104)	(0.098)	(0.074)
3.REGULATED	-0.089	-0.049		-0.005	0.118	0.012	-0.033	-0.172	0.053	-0.088	-0.049	0.228	-0.080	0.240	-0.084	0.047	0.108	-0.128
	(0.000)	(0.005)		(0.756)	(0.000)	(0.481)	(0.055)	(0.000)	(0.002)	(0.000)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)	(0.007)	(0.000)	(0.000)
4.HIGH FIXED COSTS	-0.057	-0.021	-0.005		0.026	0.515	0.162	-0.136	-0.009	-0.042	-0.070	-0.140	0.090	-0.030	-0.032	0.032	0.027	-0.023
	(0.001)	(0.225)	(0.756)		(0.128)	(0.000)	(0.000)	(0.000)	(0.620)	(0.014)	(0.000)	(0.000)	(0.000)	(0.076)	(0.062)	(0.061)	(0.118)	(0.182)
5.HIGH STD REV	0.010	-0.096	0.118	0.026		0.515	0.092	-0.026	0.100	0.064	-0.043	-0.159	0.049	-0.051	-0.002	0.054	0.013	-0.061
	(0.559)	(0.000)	(0.000)	(0.128)		(0.000)	(0.000)	(0.130)	(0.000)	(0.000)	(0.012)	(0.000)	(0.005)	(0.003)	(0.908)	(0.002)	(0.436)	(0.000)
*6.HIGH FC*HIGH STDREV*	-0.019	-0.068	0.012	0.515	0.515		0.188	-0.069	0.041	0.008	-0.047	-0.193	0.144	-0.055	0.016	0.033	-0.005	-0.036
	(0.270)	(0.000)	(0.481)	(0.000)	(0.000)		(0.000)	(0.000)	(0.016)	(0.626)	(0.006)	(0.000)	(0.000)	(0.002)	(0.362)	(0.048)	(0.771)	(0.034)
7 LOSS	0.033	-0.035	-0.033	0.162	0.092	0.188		-0.075	-0.025	-0.042	-0.096	-0.142	0.030	-0.041	-0.012	-0.208	0.017	-0.027
	(0.056)	(0.044)	(0.055)	(0.000)	(0.000)	(0.000)		(0.000)	(0.143)	(0.015)	(0.000)	(0.000)	(0.077)	(0.017)	(0.490)	(0.000)	(0.313)	(0.121)
8.HIGH INVENTORY	0.031	0.092	-0.172	-0.136	-0.026	-0.069	-0.075		0.262	0.635	0.047	-0.093	-0.066	-0.062	0.046	-0.009	-0.110	0.079
	(0.072)	(0.000)	(0.000)	(0.000)	(0.130)	(0.000)	(0.000)		(0.000)	(0.000)	(0.006)	(0.000)	(0.000)	(0.000)	(0.007)	(0.585)	(0.000)	(0.000)
9.HIGH ABI	-0.055	0.012	0.053	-0.009	0.100	0.041	-0.025	0.262		0.635	0.029	0.019	-0.044	-0.060	0.064	-0.014	-0.049	-0.005
	(0.001)	(0.468)	(0.002)	(0.620)	(0.000)	(0.016)	(0.143)	(0.000)		(0.000)	(0.094)	(0.262)	(0.011)	(0.000)	(0.000)	(0.413)	(0.005)	(0.768)
*10.HIGH INV*HIGH ABI*	0.010	0.055	-0.088	-0.042	0.064	0.008	-0.042	0.635	0.635		0.007	-0.096	-0.046	-0.051	0.030	0.006	-0.077	0.068
	(0.546)	(0.001)	(0.000)	(0.014)	(0.000)	(0.626)	(0.015)	(0.000)	(0.000)		(0.683)	(0.000)	(0.007)	(0.003)	(0.085)	(0.706)	(0.000)	(0.000)
11.HORIZON	0.010	0.116	-0.062	-0.051	-0.066	-0.042	-0.092	0.068	0.031	0.018		0.183	0.055	0.034	0.128	0.036	0.007	0.007
	(0.575)	(0.000)	(0.000)	(0.003)	(0.000)	(0.015)	(0.000)	(0.000)	(0.069)	(0.308)		(0.000)	(0.001)	(0.050)	(0.000)	(0.038)	(0.684)	(0.686)
12.SIZE = LN(ASSETS)	-0.071	0.069	0.232	-0.144	-0.155	-0.197	-0.142	-0.080	0.019	-0.087	0.206		-0.013	0.398	0.329	-0.076	0.064	0.030
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.278)	(0.000)	(0.000)		(0.455)	(0.000)	(0.000)	(0.000)	(0.000)	(0.082)
13.MB	0.146	0.079	-0.146	0.069	0.029	0.121	0.003	-0.082	-0.056	-0.076	0.125	-0.026		0.339	0.129	-0.054	-0.018	0.020
	(0.000)	(0.000)	(0.000)	(0.000)	(0.092)	(0.000)	(0.868)	(0.000)	(0.001)	(0.000)	(0.000)	(0.131)		(0.000)	(0.000)	(0.002)	(0.282)	(0.255)
14.LEV	-0.081	0.031	0.277	-0.097	-0.106	-0.141	-0.094	-0.022	-0.051	-0.051	0.038	0.560	-0.050		0.035	0.032	0.035	0.025
	(0.000)	(0.071)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.205)	(0.003)	(0.003)	(0.029)	(0.000)	(0.004)		(0.042)	(0.059)	(0.040)	(0.144)
15.LN(ANALYST)	0.026	0.064	-0.082	-0.034	-0.002	0.014	-0.012	0.045	0.062	0.030	0.142	0.318	0.208	0.044		-0.020	0.019	-0.003
	(0.124)	(0.000)	(0.000)	(0.051)	(0.888)	(0.412)	(0.482)	(0.009)	(0.000)	(0.081)	(0.000)	(0.000)	(0.000)	(0.011)		(0.239)	(0.278)	(0.859)
16.DISPERSION	-0.111	-0.046	0.053	0.032	0.092	0.044	-0.208	0.004	0.012	0.009	0.050	-0.072	-0.172	0.007	0.025		0.036	-0.034
	(0.000)	(0.008)	(0.002)	(0.061)	(0.000)	(0.010)	(0.000)	(0.803)	(0.478)	(0.587)	(0.004)	(0.000)	(0.000)	(0.675)	(0.153)		(0.034)	(0.051)
17.FOG	0.043	-0.028	0.102	0.044	0.020	0.002	0.029	-0.143	-0.062	-0.102	-0.005	0.038	0.001	0.036	0.021	0.047		-0.016
	(0.012)	(0.100)	(0.000)	(0.011)	(0.238)	(0.900)	(0.092)	(0.000)	(0.000)	(0.000)	(0.785)	(0.028)	(0.935)	(0.034)	(0.222)	(0.006)		(0.351)
18.HERF	0.072	-0.004	-0.261	-0.005	-0.110	-0.036	-0.017	0.138	0.024	0.107	0.036	-0.065	0.093	-0.077	-0.015	-0.061	-0.053	
	(0.000)	(0.794)	(0.000)	(0.779)	(0.000)	(0.036)	(0.328)	(0.000)	(0.160)	(0.000)	(0.039)	(0.000)	(0.000)	(0.000)	(0.383)	(0.000)	(0.002)	

Notes to Table 4:
This table reports the Pearson (Spearman) correlation on the upper (lower) diagonal. Two tailed p-values are presented in parentheses. All variables are defined in Appendix 1. All continuous variables are winsorized at the extreme 1%.

TABLE 5

Logistic regressions modeling the probability that management's annual earnings forecasts are more accurate than analysts' forecasts

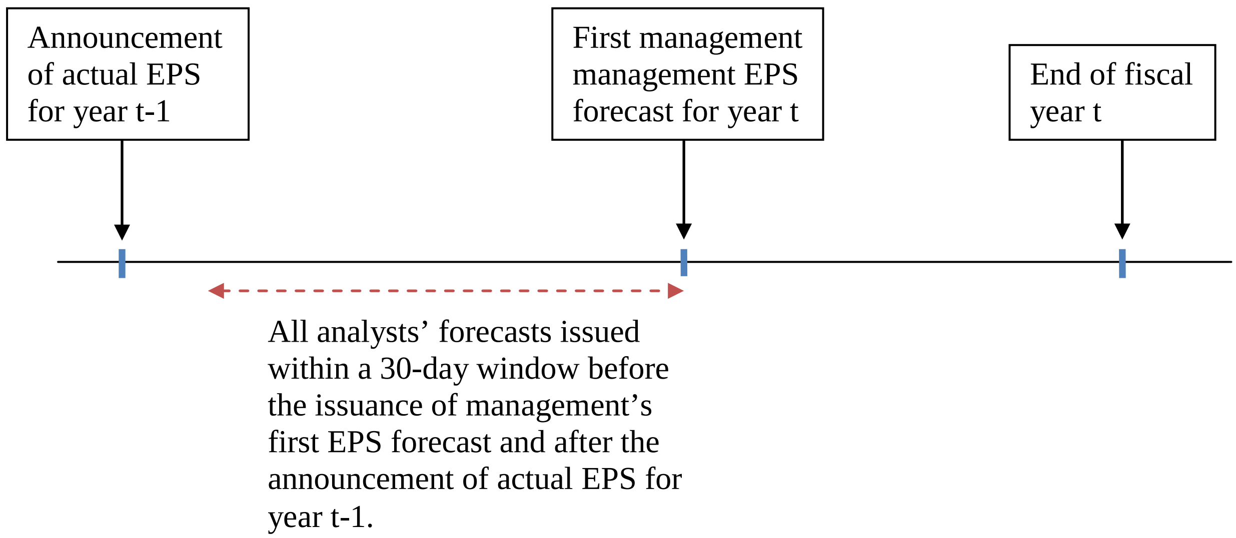
$Pr(MGR_{i,t}=1) = f\,(CYCLICALITY_{i,t-1}, HIGH\ REV\ SYNC_{i,t-1}, REGULATED_{i,t}, HIGH\ FIXED\ COSTS_{i,t-1},$
$HIGH\ STD\ REV_{i,t-1}, HIGH\ FIXED\ COSTS{*}\ HIGH\ STD\ REV_{t-1}, LOSS_{i,t}, HIGH\ INVENTORY_{i,t-1},$
$ABI_{i,t-1}, HIGH\ INVENTORY{*}ABI_{i,t-1}, HORIZON_{i,t}, LN(TOTAL\ ASSETS)_{i,t-1}, MB_{i,t-1}, LEVERAGE_{i,t-1},$
$LN(ANALYST)_{i,t}, DISPERSION_{i,t-1}, FOG\ INDEX_{i,t-1}, HERFINDAHL_{i,t})$

Variable	**Predicted Sign**	**(3)**		**Marginal Impact based on (3)**
		Coefficient	**Z-stat**	
INTERCEPT		0.706	1.53	
CYCLICALITY	-	-0.433	-3.17***	-0.045
HIGH REV SYNC	-	-0.118	-1.69*	-0.029
REGULATED	-	-0.290	-2.05**	-0.071
HIGH FIXED COSTS		-0.145	-1.52	-0.036
HIGH STD REV		-0.175	-1.78*	-0.043
*HIGH FIXED COSTS * HIGH STD REV*	+	0.277	1.72*	0.069
LOSS	+	0.503	1.95*	0.125
HIGH INVENTORY		0.038	0.45	0.009
HIGH ABI		-0.809	-1.42	-0.196
*HIGH INVENTORY * HIGH ABI*	+	1.441	2.26**	0.337
HORIZON	-	-0.002	-3.02***	0.046
SIZE = LN(ASSETS)		-0.015	-0.51	-0.008
MB		-0.018	-1.53	0.010
LEVERAGE		0.024	1.26	0.008
ANALYST FOLLOWING =LN(ANALYST)		0.089	1.29	0.040
DISPERSION		0.415	1.10	0.004
FOG INDEX		-0.005	-0.27	-0.002
HERFINDAHL		-0.930	-1.15	-0.006
N		3,387		
Pseudo R^2		2.05%		

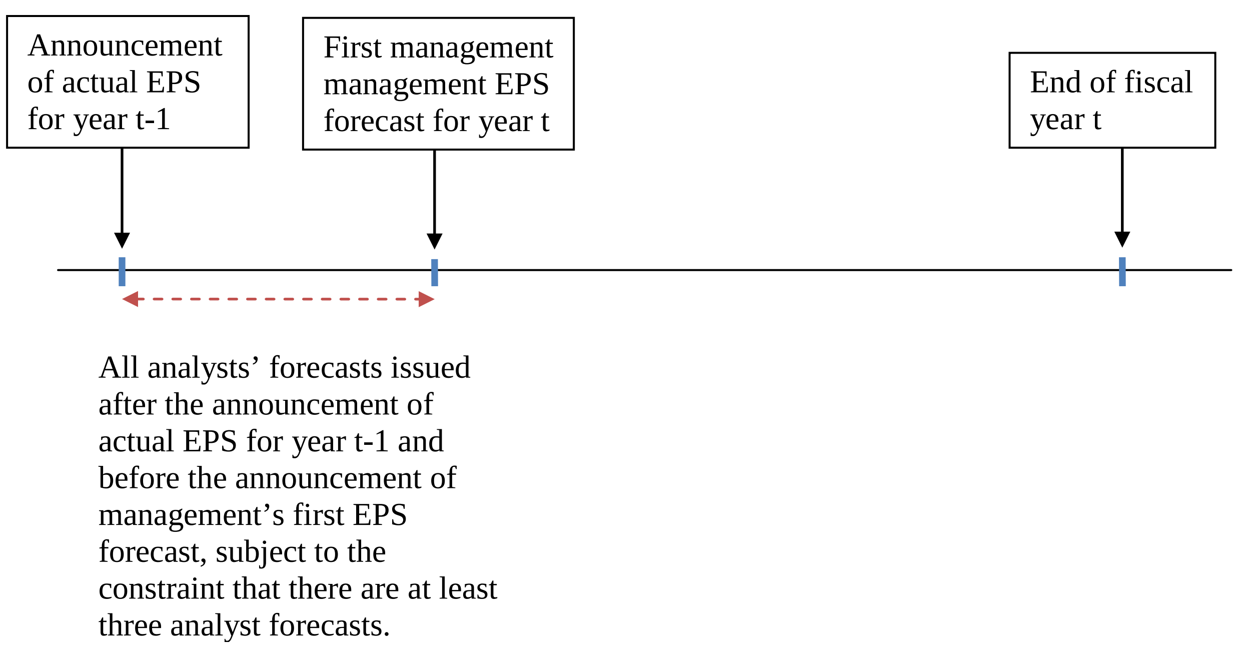
Notes to Table 5:
All variables are defined in Appendix 1. All continuous variables are winsorized at the extreme 1%. *, ** and *** represent significance at 10%, 5% and 1% (2-tailed). Standard errors are clustered by firm. The magnitude and standard error of *HIGH FIXED COSTS * HIGH STD REV* and *HIGH INVENTORY*HIGH ABI* are estimated based on Ai and Norton (2003). Marginal impact is the expected change in the probability of having a more accurate management forecast (MGR=1) resulting from an increase in each independent variable from the 25^{th} to the 75^{th} percentile of the sample distribution when it is a continuous variable, and from 0 to 1 if it is an indicator variable, while holding all other independent variables at their means.

FIGURE 1
Timing of Management and Analyst Forecasts

Scenario A: Management's first EPS forecast for year t is issued at least 30 days *after* the announcement of actual EPS for year t-1



Scenario B: Management's first EPS forecast for year t is issued *less than* 30 days *after* the announcement of actual EPS for year t-1.



APPENDIX 1

Variable definitions (Compustat data items in parentheses):

MGR	Indicator variable set to 1 when the absolute value of the management forecast error is smaller than the absolute value of the analyst forecast error. Management forecast error is measured as the first management earnings forecast for year t issued after the actual announcement for earnings in year t-1, minus the actual earnings for year t. Analyst forecast error is measured as the mean of all analyst forecasts issued thirty days before the first management forecast minus the actual earnings. The variable is set to 0 otherwise.
CYCLICALITY	Cyclicality is measured as the R^2 from the firm-level estimation of the model over the prior 12 quarters: $EARN_{i,t} = \alpha_0 + \alpha_1\ GDP_t + \varepsilon_{i,t}$ where *EARN* is defined as income before extraordinary item (ibq) and *GDP* is the nominal quarterly Gross Domestic Product.
REVENUE SYNCHRONICITY (REV SYNC)	Revenue synchronicity is measured as the R^2 from the firm-level estimation of the model over the prior 12 quarters: $REV_{i,t} = \alpha_0 + \alpha_1\ INDREV_t + \varepsilon_{i,t}$ where *REV* is defined as revenue (saleq) divided by last quarter's revenue and *INDREV* is sum of *REV* for all firms in the industry. The industry classification is based on Fama and French (1997).
REGULATED	Indicator variable set to 1 if the firm operates in a regulated industry, defined as the four-digit SIC codes 4900-4999 (utilities), 6000-6099, 6100-6199 (banking), and 6200-6299, 6700-6799 (financial institutions), 0 otherwise.
COST STRUCTURE	For each firm year, we estimate the coefficient (β_1) from the firm-level model over the prior 12 quarters: $LOG(EXP_t / EXP_{t-1}) = \beta_0 + \beta_1 LOG(REV_t / REV_{t-1}) + \varepsilon_{i,t}$ based on Anderson et al. (2003) where *REV* is defined as revenue (saleq) and *EXP* is defined as revenue (saleq) minus income before extraordinary item (ibq). The final variable, COST STRUCTURE, is the coefficient (β_1) for each firm minus the mean coefficient (β_1) for all firms in the same industry in that year. The industry classification is based on Fama and French (1997).
HIGH FIXED COST	Indicator variable set to 1 if the firm is in the bottom tercile of *COST STRUCTURE* and set to 0 otherwise.
REVENUE VOLATILITY =(STD REV)	Standard deviation of revenue (saleq) measured over the prior 12 quarters scaled by the mean revenue over the same time period.
HIGH STD REV	Indicator variable set to 1 if the firm is in the top tercile of *REVENUE VOLATILITY* and set to 0 otherwise.
LOSS	Indicator variable set to 1 if the management forecast is less than 0 and set to 0 otherwise.
INVENTORY	Inventory (invt) divided by total assets (at).
HIGH INVENTORY	Indicator variable set to 1 if the firm is in the top tercile of *INVENTORY* and set to 0 otherwise.
ABNORMAL INVENTORY (ABI)	Normalized deviation from the industry days inventory measured as (DI_{it} – Industry mean DI_t) /Industry standard deviation of DI_t where DI = inventory (invt) * 365) / cost of goods sold (cogs). This measure is based on Chen et al. (2005) and Kesavan and Mani (2010). Industry classification is based on Fama and French (1997).
HIGH ABI	Indicator variable set to 1 if the firm is in the top tercile of *ABI* and set to 0 otherwise.
HORIZON	Number of days between the date of the management forecast and the end of the fiscal year.
SIZE = LN(ASSETS)	Natural logarithm of total assets (at).

APPENDIX 1 (CONTINUED)

Variable definitions (Compustat data items in parentheses):

MB	Market value of equity (prcc_f*csho) divided by book value of equity (ceq).
LEVERAGE	Total assets (at) divided by book value of equity (ceq).
ANALYST FOLLOWING = LN(ANALYST)	Natural logarithm of the number of analyst forecasts issued thirty days before the management forecast.
FOG INDEX	Readability of prior period's 10-K filings based on Li (2008).
HERFINDAHL	Herfindahl Index is a measure of industry concentration and is defined as $\sum_{i=1}^{N} MKTSHARE_i^2$ where *MKTSHARE* is the market share for each firm in the industry. Market share for firm I is measured as the revenue for firm I divided by total revenue for all firms in the industry. Industry classification is based on Fama and French (1997).
MFERROR	Management forecast error is measured as the first management EPS forecast for year t after the actual announcement for earnings in year t-1 minus the actual EPS for year t, all divided by actual EPS.
AFERROR	Analyst forecast error is measured as the mean of all analyst EPS forecasts issued thirty days before the first management EPS forecast for year t minus the actual EPS, all divided by actual EPS.

APPENDIX 2

Descriptive Statistics by Industry

Panel A: Mean and Median Cyclicality by Industry

INDUSTRY	CYCLICALITY	
	Mean	Median
Aircraft	**0.437**	**0.348**
Agriculture	0.250	0.204
Automobiles and Trucks	0.219	0.142
Banking	0.425	0.370
Alcoholic Beverages	0.147	0.128
Construction Materials	0.252	0.190
Printing and Publishing	0.236	0.187
Shipping Containers	0.196	0.138
Business Services	0.294	0.209
Chemicals	0.241	0.155
Electronic Equipment	0.388	0.337
Apparel	0.234	0.182
Construction	**0.425**	**0.453**
Coal	0.242	0.294
Computers	0.326	0.251
Pharmaceutical Products	0.246	0.145
Electrical Equipment	0.413	0.443
Petroleum and Natural Gas	0.336	0.266
Fabricated Products	0.326	0.400
Trading	0.399	0.385
Food Products	0.152	0.100
Entertainment	0.205	0.167
Precious Metals	0.153	0.060
Defense	**0.457**	**0.352**
Healthcare	**0.469**	**0.460**
Consumer Goods	0.261	0.189
Insurance	0.348	0.279
Lab Equipment	0.316	0.239
Machinery	0.348	0.252
Restaurants, Hotel, Motel	0.277	0.190
Medical Equipment	0.313	0.230
Nonmetallic Mining	0.116	0.027
Miscellaneous	0.000	0.000
Business Supplies	0.268	0.195
Personal Services	0.316	0.176
Retail	0.231	0.169
Real Estate	0.149	0.146
Rubber and Plastic Products	0.178	0.131
Shipbuilding, Railroad	**0.843**	**0.900**
Tobacco Products	0.050	0.049
Candy and Soda	0.096	0.043
Steel Works	0.343	0.287
Telecommunications	0.310	0.284
Recreational Products	0.293	0.210
Transportation	0.337	0.261
Textiles	0.303	0.303
Utilities	0.117	0.051
Wholesale	0.386	0.318

Notes to Appendix 2 Panel A:
The industry classification is based on Fama and French (1997). The top five industries with the highest mean cyclicality are in bold.

APPENDIX 2 (CONTINUED)
Descriptive Statistics by Industry

Panel B: High and Low Levels of Revenue Synchronicity by Industry

INDUSTRY	REVENUE SYNCHRONICITY				TOTAL
	LOW		HIGH		
	No. of observations	Percentage	No. of observations	Percentage	No. of observations
Aircraft	**9**	**25**	**27**	**75**	**36**
Agriculture	7	44	9	56	16
Automobiles and Trucks	30	60	20	40	50
Banking	21	78	6	22	27
Alcoholic Beverages	**2**	**13**	**13**	**87**	**15**
Construction Materials	31	58	22	42	53
Printing and Publishing	**8**	**20**	**32**	**80**	**40**
Shipping Containers	10	50	10	50	20
Business Services	253	49	260	51	513
Chemicals	37	56	29	44	66
Electronic Equipment	54	45	65	55	119
Apparel	46	48	50	52	96
Construction	**14**	**20**	**57**	**80**	**71**
Coal	3	75	1	25	4
Computers	55	45	67	55	122
Pharmaceutical Products	98	56	78	44	176
Electrical Equipment	30	53	27	47	57
Petroleum and Natural Gas	32	78	9	22	41
Fabricated Products	17	89	2	11	19
Trading	40	51	38	49	78
Food Products	42	69	19	31	61
Entertainment	34	74	12	26	46
Precious Metals	3	100	0	0	3
Defense	**3**	**19**	**13**	**81**	**16**
Healthcare	58	74	20	26	78
Consumer Goods	42	58	30	42	72
Insurance	84	71	35	29	119
Lab Equipment	29	36	51	64	80
Machinery	46	41	67	59	113
Restaurants, Hotel, Motel	71	70	30	30	101
Medical Equipment	77	55	64	45	141
Nonmetallic Mining	7	50	7	50	14
Miscellaneous	0	0	0	0	0
Business Supplies	30	71	12	29	42
Personal Services	22	40	33	60	55
Retail	**75**	**22**	**271**	**78**	**346**
Real Estate	**0**	**0**	**6**	**100**	**6**
Rubber and Plastic Products	8	44	10	56	18
Shipbuilding, Railroad	3	50	3	50	6
Tobacco Products	2	40	3	60	5
Candy and Soda	**0**	**0**	**10**	**100**	**10**
Steel Works	16	64	9	36	25
Telecommunications	35	60	23	40	58
Recreational Products	13	62	8	38	21
Transportation	37	54	31	46	68
Textiles	2	100	0	0	2
Utilities	100	58	72	42	172
Wholesale	57	63	33	37	90

Notes to Appendix 2 Panel B:
The industry classification is based on Fama and French (1997). Industries with 75% or more of the firms in the high revenue synchronicity group are in bold.

APPENDIX 2 (CONTINUED)
Descriptive Statistics by Industry

Panel C: Each cell reports the number of firm years with low, medium and high levels of inventory by industry.

	Level of Inventory as Percentage of Total Assets (HIGH INVENTORY)			TOTAL
	LOW	**MEDIUM**	**HIGH**	
Retail	2 (0.60%)	50 (15.15%)	278 (84.24%)	330
Manufacturing	65 (4.79%)	659 (48.53%)	395 (46.69%)	788
Others	1,164 (62.62%)	369 (21.72%)	166 (9.77%)	1699
TOTAL	637	637	637	**3387**

Notes to Appendix 2 Panel C:
The number of observations in each cell relative to the total number of observations in the particular industry is reported as a percentage in the brackets. Retail is defined as the two-digit SIC codes 52 (lumber and other building materials), 53 (general merchandise stores), 54 (food stores), 55 (automotive dealers and service stations), 56 (apparel and accessory stores), 57 (home furnishing stores) and 59 (miscellaneous retail). Manufacturing is defined as the two-digit SIC codes 20 (food and kindred products), 21 (tobacco products), 22 (textile mill products), 23 (apparel and other textile products), 24 (lumber and wood products), 25 (furniture and fixtures), 26 (paper and allied products), 27 (printing and publishing), 28 (chemicals and allied products), 29 (petroleum and coal products), 30 (rubber and misc plastics products), 31 (leather and leather products), 32 (stone, clay and glass products), 33 (primary metal industries), 34 (fabricated metal products), 35 (industrial machinery and equipment), 36 (electronic and other electric equipment), 37 (transportation equipment), 38 (instruments and related products), and 39 (miscellaneous manufacturing).